PostScript

LETTERS

Overdispersion in health care performance data: Laney's approach

The use of statistical process control (SPC) based methods is increasing in health care.[1 2] One issue that raises concern is that of overdispersion.[3] Overdispersion, which often occurs when sample sizes are very large, is said to occur when the control limits are very close to each other leading to the identification of an ''inappropriately'' large number of data points signalling special cause variation. Overdispersion is not new to the general SPC literature,[4–6] but it has been highlighted recently in healthcare applications of SPC by Spiegelhalter.[3]

Spiegelhalter explored a number of possible statistical and non-statistical strategies for dealing with overdispersion, favouring on balance a random effects modelling approach. We wish to highlight another approach to handling overdispersion which was developed by Laney.[6] We illustrate this approach by using the proportion of emergency readmissions following live discharge data for 2002 from the NHS Performance Ratings dataset.[7]

In SPC the conventional control chart for handling a time sequence of proportions is the p-chart. Laney showed how to measure and correct for overdispersion in cases where the parameter p (event probability) is not constant but changes over time, thereby resulting in overdispersion. Laney's solution was the development of a p′-chart[6] which supplements the usual computation of binomial sampling variance with an additional component of variance due to the fluctuation in the parameter p over time.

However, Spiegelhalter focused primarily on healthcare performance data which were cross-sectional (that is, not a time sequence).[3] Fortunately, there is a variant of the p-chart known as the funnel plot[8] which can be used in such cases. Using such a chart, the proportion of readmissions produces the plot shown in the left graph in fig 1 with 3-sigma control limits. There is clear evidence of overdispersion.

The difficulty with the conventional (binomial) funnel chart is that it concerns itself only with the variation *within* hospitals and ignores the variation *between* hospitals. Application of a similar approach to that used in Laney's p′-chart provides a simple solution. As in the p′-chart, we can use both sources of variation (within and between hospitals) in deriving the 3-sigma control limits. While Laney's solution for time sequence data uses the average moving range for the between unit variance, it can be easily modified to the case where there is no time order in the data merely by substituting the classical root mean square variance formula.

We illustrate the derivation of control limits for Laney's p′-chart using the following notation: p_i is the proportion of re-admissions in hospital i, n_i is the number of discharges in hospital i, σ_{pi} denotes the standard deviation of p_i which, assuming a binomial distribution, is given by:

$$\sigma_{pi} = \sqrt{\bar{p}(1-\bar{p})/n_i}$$

where $\bar{p}$ is the overall proportion of readmissions and z_i is the z score in standard deviations of p_i and is given by $z_i = (p_i - \bar{p})/\sigma_p$ and σ_z is the standard deviation of z which, for time ordered data, is derived by using the moving range approach (as described in standard SPC texts).[9] However, in this case where there is no time order to the data, σ_z may be determined using the classical standard deviation formula based on the root mean square of the deviances:

$$\sigma_z = \sqrt{\sum (z_i - \bar{z})^2/(N-1)}$$

where N is the sum of n_i and $\bar{p}\pm$ is the mean of $z_{i.}$

The 3-sigma control limits for Laney's p′-chart are thus given by $\bar{z}$ 3 σ_{pi} $\sigma_{z,}$ thereby accounting for within and between hospital variations. The resulting 3-sigma control limits are shown in the right panel of fig 1 and appear to ''correct'' for the overdispersion.

There are number of issues relating to Laney's p′-charts.[6] In the absence of overdispersion, σ_z will be close to 1, so the limits produced by a conventional p-chart and Laney's p′-charts will be similar. Their routine use therefore appears to be without obvious adverse consequences. [Note: In time sequence applications, σ_z can take on values less than 1 if there is positive serial correlation in the data. Since no such condition exists for cross-sectional data, σ_z should have a minimum value of 1 in such applications.] Although we have illustrated Laney's p′-chart using binomial data, Laney's method easily extends to the Poisson case[6] (known as the u-chart in SPC terminology). Furthermore, Laney's p′-chart dovetails elegantly with traditional SPC approaches, perhaps making it more straightforward to implement by those familiar with traditional SPC methods.

As Spiegelhalter[3] has described, there may be several statistical approaches to dealing with overdispersion. While it may be reasonable to undertake desktop comparisons of these different statistical approaches by using existing or simulated data sets, we need to recognise that the ultimate evidence as to the effectiveness (including costs) or otherwise of different methods can only be determined empirically. Finally, we caution against the desktop adjustment of data without scientific investigations into the ''causes'' of overdispersion, recalling that the basic aim of SPC is to support continual improvement and not the construction of optimum statistical models.

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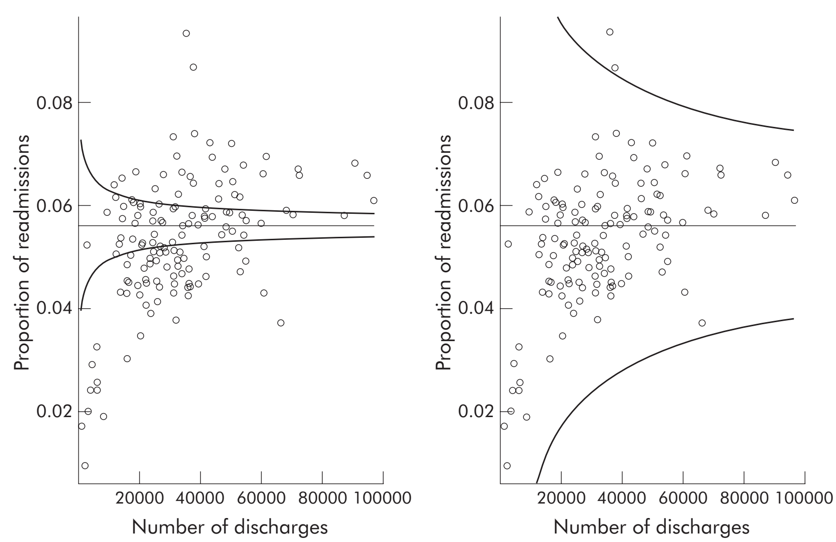

Figure 1 Charts showing proportion of readmissions following live discharges from hospitals in the NHS.[7] Left panel is a conventional p-chart which shows overdispersion. Right panel is Laney's p′-chart which corrects for overdispersion.

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Changing social relationships

In his review of our paper on pro-anorexia internet communities,[1] Dr Smith introduced one inaccuracy into an otherwise concise summary. He mistakenly attributed a quotation from a participant in the internet forum to our researcher. Angela (a pseudonym) had commented that she was intending to leave the group because she did not approve of some of the comments made by other participants. Dr Smith put these words in the mouth of our own Dr Ward and then wondered why she had decided to stop her research.

This interpretation gives a slightly misleading overall impression of our own response to the pro-anorexia community. Whatever our own feelings about the philosophy of the group, our analysis sought to provide as objective an understanding of the participants' views as possible. We concluded our paper by suggesting that there is a coherent model of anorexia behind the pro-anorexia movement, and that, to comprehend this apparently irrational desire to sustain very low body weight, it is necessary to understand this model first.

We hope this clarification will assist readers in making sense of our research and perhaps to take a look at the original paper.[2]

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Situational awareness in medicine

As a retired United States Air Force pilot-physician, I commend Singh *et al* for their excellent use of situational awareness as an analysis tool in aviation.[1] I wish only to add a subtle dimension to their illustration of situational awareness: LSA (loss of situational awareness) began as a universally recognised acronym of the North Atlantic Treaty Organization. But one cannot lose what one never had. Situational awareness in military and air carrier aviation universally begins at a maximum, and may deteriorate backwards from level 3 of Endsley's model. Maximal situational awareness at the outset of a mission is achieved by all team members studying environmental factors that might affect the outcome; mentally rehearsing the mission timeline, actions and threats; and planning for contingencies during the pre-flight briefing. The team begins with a high-level, mental model of what is to come. Sadly, pre-event reviews are becoming increasingly rare in medicine, and doctors begin with very limited or no situational awareness as illustrated by the outpatient case in the paper. Further, situational awareness in outpatient medicine, if it exists at all, is compromised by the fragmentation and time displacement of cues and communications. Ironically, it is easier to discern situational awareness, good and bad, in the confines of the high-risk areas of inpatient care: the operating room, labour and delivery, and the emergency department. Medical team training courses emphasise the value of briefings in setting the stage for good situational awareness, and train high-risk team leaders to conduct them.

Thus far, team training is not widely deployed or accepted. Nor are briefings cited in such patient-safety resources as the Agency of Healthcare and Research Quality Web Morbidity and Mortality. Another fundamental, but subtle, difference between aviation and medicine is decision making. The hapless primary care physician was ''flying solo'' and making independent judgements. Despite the Hollywood images, fighter pilots rarely make solo decisions. Flying in multiples for mutual support, air combat teams operate with strong, visible, designated leadership, but simultaneously practise collaborative, consensus decision making. Similarly, ''cockpit resource management'', the progenitor of medical team training, reversed decades of left-seat, hierarchical, autocratic decisions that placed passengers at the same risk level as the described patient in favour of collaborative decision making after inputs by all, even by passengers.[2] Lastly, the authors omit any discussion of a post-event debriefing of this adverse outcome. Thus, learning was not captured; nor were system improvements made. Debriefings—as short as 30 s or lasting for hours—are mandatory in aviation and result in real-time, actual, lasting continuous quality improvement. Early efforts to use traditional Morbidity and Mortality conferences offer some promise in debriefings). Medicine has much to adopt and adapt from other high-risk professions, aviation, nuclear power and even mining. The authors have advanced that journey considerably.

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We thank Dr McCarthy for his thoughtful insights on the application of situational awareness in medicine. We agree that doctors begin with a limited amount of situational awareness and often fail to maximise their situational awareness using a team approach. Owing to the increasing complexity and acuity of care in the outpatient setting, the risk of outpatient medical errors has increased during the past several years.[1] Thus, the use of situational awareness in outpatient care has become more critical than ever. Although doctors function at times with a high degree of situational awareness, they seldom continue to be ''aggressively sceptic'' in the environment of outpatient care, owing to factors such as fragmented communication, as Dr McCarthy noted. In our article, we propose that achieving ''team situational awareness'' could overcome some of these obstacles. Team situational awareness can act as a safety net for primary care doctors ''flying solo'' and can be facilitated by a culture change in communication among doctors.

We do acknowledge the omission of a post-event debriefing in our discussion. Nevertheless, we believe that learning resulted from this case to some extent. We discussed the case in detail at a traditional conference on morbidity and mortality and communicated several lessons to the audience. Unfortunately, as many doctors would agree, the quest to make systems improvements and policy changes based on isolated ''stories'' is not always successful.[2] Unlike aviation, medicine seeks evidence from randomised controlled trials and other evidence-based literature to change healthcare systems. With decreasing funding opportunities to support research on medical error management, we hope that cases such as ours illustrate the learning opportunities from other high-risk industries.

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